The Manufacturer's AI Adoption Playbook

A practical path to AI value

IFS.ai

Most AI playbooks promise transformation. This one delivers action.

Manufacturing leaders know AI matters. But between the promise and the performance lies a gap, filled with complexity, confusion, and competing priorities.

This playbook provides a clear path forward. It outlines a structured approach to pilot your first AI use case and demonstrate measurable value.

What's inside

- A proven framework to pick your first AI win
- Real examples from the field (what works, what doesn't)
- Structured implementation roadmap
- Practical tools to get started today

Let's build something that works.

Step 1

Pick your battle

The quick-win matrix

Instructions: Score each factor from **1 to 5 points** (1 = not ready, 5 = ideal conditions).

The golden rule

Start where you have data, pain, and a champion. Missing any of these? Pick a different battle.

	Capability			
Why it matters	**Not ready** 1 point	**Getting There** 3 points	**Ready to Go** 5 points	**Your Score**
Data available Can't train AI without it	Paper records only	Some digital, gaps exist	2+ years of clean digital data	
Pain level No pain=No priority	Minor inconvenience	Regular headaches	Major operational issue	
Champion Owner	"Someone should look at this"	Manager interested	Operations leader committed	
Scope contained Start small to win	Multiple sites/ systems	Entire department	Single line/ machine/process	
			Total Score:	

Interpreting your total:

Below 12: Not ready – Find a more valuable use case

12-15: Close but not quite – Address gaps

16-20: Ready to start – Proceed

Top 5 manufacturing AI quick win examples

1 Predictive maintenance

- **Start with:** Your most critical breakdown (e.g., main production line conveyor, CNC spindle failure, packaging equipment)
- **Data needed:** Sensor data + maintenance logs
- **AI action:** Detect anomaly patterns that predict failure 3-7 days before breakdown
- **Typical result:** Measurable decrease in downtime
- **Speed:** Quick win

2 Quality prediction

- **Start with:** Highest scrap rate product
- **Data needed:** Process parameters + quality tests
- **AI action:** Predict defects during production based on parameter combinations
- **Typical result:** Significant defect reduction
- **Speed:** Moderate implementation

3 Energy optimization

- **Start with:** Highest energy process
- **Data needed:** Utility meters + production data
- **AI action:** Identify optimal settings and scheduling to minimize energy use while maintaining output
- **Typical result:** Noticeable energy reduction
- **Speed:** Quick win

Top 5 manufacturing AI quick win examples (cont.)

4 Demand sensing

- **Start with:** Most volatile SKU
- **Data needed:** Sales history + external factors (seasonality, promotions, market trends)
- **AI action:** Detect demand signals earlier and adjust production planning accordingly
- **Typical result:** Improved forecast accuracy
- **Speed:** Longer implementation

5 Changeover optimization

- **Start with:** Longest changeover
- **Data needed:** Changeover logs + sequences (product A to B times, setup steps, tool changes)
- **AI action:** Find optimal changeover sequences and predict setup times for better scheduling
- **Typical result:** Reduced changeover time
- **Speed:** Quick win

Step 2

Get it done

Data reality check

Most AI pilots can start with existing data, even if it has some gaps.

Quck Data Audit:

- Can you access the data? (If no–fix this first)
- Is it digital? (If no–can you digitize 3 months?)
- Any obvious gaps? (If yes–can you work around them?)
- Is data captured automatically? (If no–connect sensors/PLCs to database)

Common surprises:

"We track that" ≠ "It's in a database"

Excel everywhere = 2 extra weeks to consolidate data

Different data formats = Need to standardize units, dates, naming

Missing history = Start collecting today or pick different use case

Build your team

Why this matters: AI projects fail without the right people. You need technical knowledge and operational expertise, but most critically someone with actual authority to make decisions. No authority = endless meetings with no action.

Common team structure that works

Champion

Who: Someone who lives with the problem daily and understands its full impact

Role: Drives the project, escalates barriers, owns the outcome

Data wrangler

Who: IT/OT person who knows your systems

Role: Data access, integration

Process expert

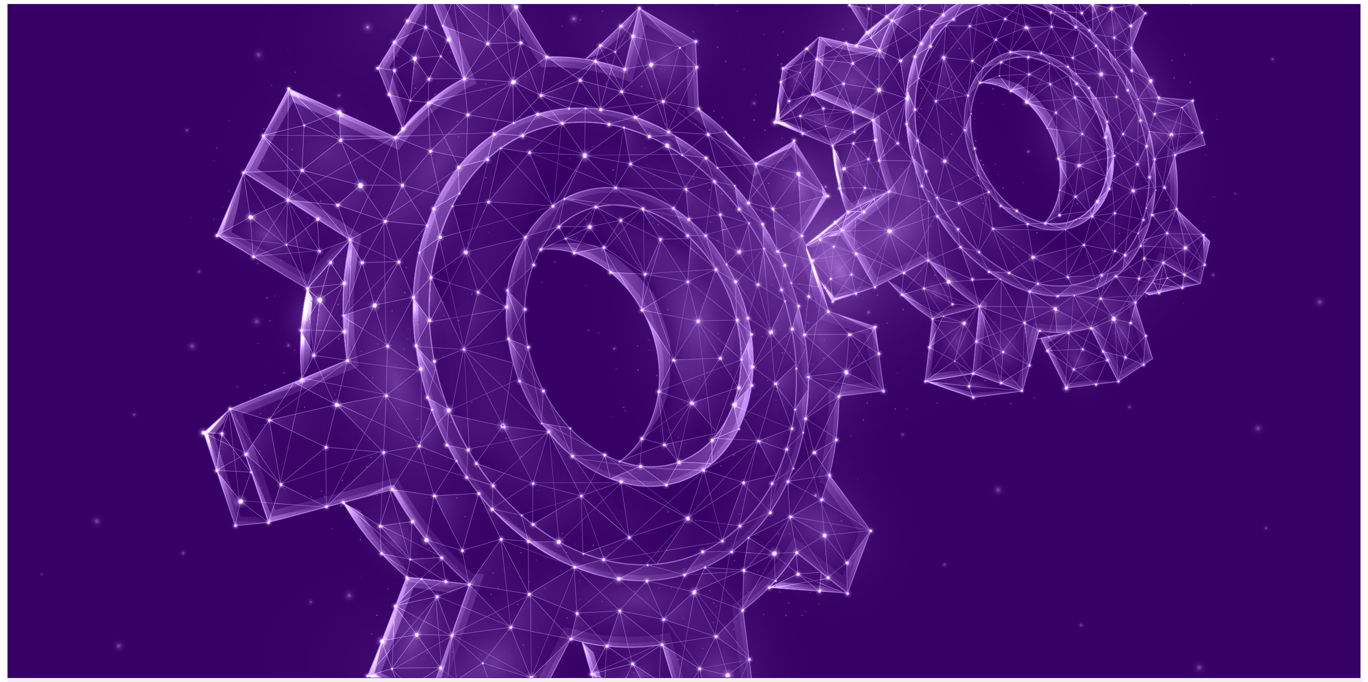
Who: Senior operator/engineer

Role: Reality checker, validator

AI partner (Optional)

Who: IFS team or approved partner

Role: Model building, deployment



Build and test

Crawl:

- Build simplest possible model
- Test on historical data
- Aim for "better than guessing"

Walk:

- Refine based on learning
- Test on recent data
- Aim for "better than current method"

Walk:

- Deploy parallel to current process
- Compare predictions to reality
- Aim for "trust it enough to act"

Example

Predictive maintenance on a critical pump

Prove Value

What to measure:

- Primary metric (downtime, defects, energy)
- Cost savings (hard dollars only)
- Time savings (operator hours, setup time, planning time)
- Near misses prevented

How to report:

- Gather initial results
- Build simple dashboard
- Focus on: Before vs. after
- Include: Wins and misses

Crawl:

Build basic model using vibration data from past 6 months. Model says “high vibration = check pump.” Catches 60% of failures in historical data, better than the current 0%.

Walk:

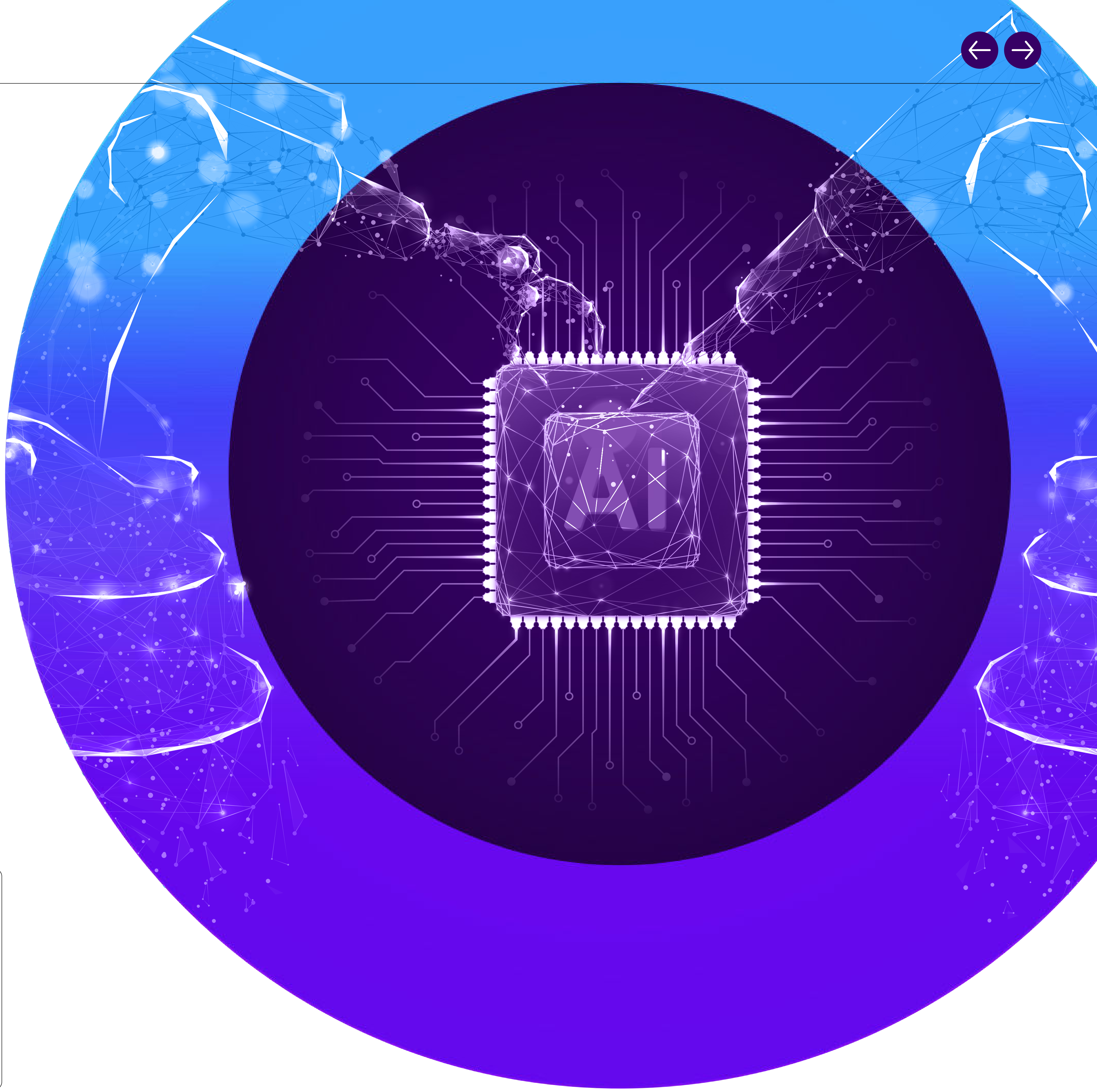
Add temperature and pressure data. Refine to predict “failure likely in next 7 days.” Now catching 75% of recent failures with 2-day advance warning.

Run:

Deploy alongside current monthly inspections. When model alerts, maintenance checks pump. After 30 days: prevented 3 breakdowns, 1 false alarm. Team starts trusting alerts.

Example reporting elements:

- **Before:** 12 unplanned stops/month → After: 7 stops/month
- **Wins:** Caught bearing failure 3 days early, saved 8-hour breakdown
- **Misses:** 2 false alarms caused unnecessary checks
- **Key metric:** 42% reduction in unplanned downtime
- **Next steps:** Review false alarm data, adjust alert thresholds, add more sensor inputs



Common pitfalls (and how to avoid them)

"Let's do everything!"

Symptom:
Scope grows weekly

Fix:
Write down scope. Don't change for 90 days.

Remember:
"Phase 2" is your friend

"Our data is too messy"

Symptom:
Endless cleanup projects

Fix:
Set 2-week cleanup limit

Remember:
Good enough beats perfect later

"The operators won't use it"

Symptom:
Great model, no adoption

Fix:
Include operators from day 1

Remember:
Build the solution with operators as partners, not something imposed on them

"IT says it's not secure"

Symptom:
Security review purgatory

Fix:
Involve IT week 1, not week 11

Remember:
Get ahead of security concerns early to avoid last-minute roadblocks1

"The ROI isn't clear"

Symptom:
Can't prove the AI made a difference

Fix:
Measure baseline performance before starting

Remember:
Without "before" data, you can't show improvement

Making it real

What success looks like

Realistic pilot outcomes:

- Model accuracy: 75-85% (not 99%)
- Adoption rate: 60-80% (not 100%)
- ROI clarity: Trending positive
- Team sentiment: "Let's do another"

From pilot to program

Early expansion:

1. Document what worked
2. Pick Pilot #2 (different problem)
3. Build internal capability
4. Create templates for pilots 3-10

What success looks like

- 3-5 pilots running
- Clear patterns emerging
- ROI proven and tracked
- Executive buy-in secured

Example progession

Automotive parts manufacturer:

Pilot 1: Predictive maintenance

- **Problem:** Paint booth failures causing 20+ hours downtime monthly
- **Solution:** Gave model 6 months of sensor data (vibration, temperature, motor current) plus maintenance logs showing when failures occurred. The model learned that a specific combination (slight vibration increase + temperature rise of 2°C + motor current fluctuation) appears 3-5 days before bearing failure. Maintenance team now gets alerts to check bearings before they fail.
- **Result:** 35% reduction in booth downtime
- **Learning:** Need operator training on alert response

Pilot 2: Quality prediction

- **Problem:** 12% scrap rate on complex molded parts
- **Solution:** Connected model to 20 process variables (mold temperature, injection pressure, cooling time, material batch, etc.) and quality test results. Model discovered that when injection pressure varies >2% while mold temperature is above 185°C, defect rate jumps to 31%. System now alerts operators to adjust settings before making bad parts.
- **Result:** 28% fewer defects by adjusting parameters mid-production
- **Learning:** Process data more valuable than expected

Pilot 3-5: Broader expansion

- **Problem:** High energy costs, 4-hour changeovers, demand volatility
- **Solution:**

  Energy: Model analyzed 12 months of production schedules and utility rates, found that shifting heavy processes to start 30 minutes earlier avoids peak rates

  Changeovers: Model studied 500+ changeover logs, identified that sequencing by color (light to dark) and material type reduces cleaning time by 45 minutes

  Demand: Model combined 2 years of order history with customer planning data, now predicts demand spikes 2 weeks out vs. reacting after orders arrive
- **Combined impact:** $2.1M annual savings identified
- Organization now has internal AI champions in each plant
- Standard process for evaluating and launching new use cases

Understanding AI capabilities

AI excels at:

- Finding patterns easily missed: Can spot that multiple variables changing together predict failure, even when each looks normal alone.
- Consistent decisions: Applies same rules without fatigue or distraction–though models need monitoring for drift over time.
- Processing many variables: Analyzes all available factors simultaneously to find complex relationships.
- Learning from outcomes: Gets smarter with each failure/success, automatically adjusting predictions.

AI can't:

- Fix broken processes: If your changeover process is flawed, AI can only optimize within those constraints.
- Replace expertise: Still need operators who understand why decisions matter and when to override.
- Work without data: No historical data = no patterns to learn. Can't predict what it's never seen.
- Manage change: Won't convince skeptical operators or navigate organizational politics. Requires leadership, communication, and buy-in at all levels.

Your next steps

Just exploring?

1. Run the quick-win matrix on 3-5 problems
2. Talk to peers who've done this
3. Join IFS webinars or local IFS Connect events
4. Connect with an IFS AI expert

Ready to start?

1. Pick your highest-scoring opportunity
2. Assign your champion
3. Build your implementation plan
4. Commit to your first pilot

Stuck somewhere?

- **No clear use cases:** Start with maintenance
- **No data access:** Fix this first. It's worth the effort
- **No budget:** Start small with a focused pilot
- **No support:** Find a new champion
- **Need expertise:** Consider IFS Nexus Black for rapid deployment support

The bottom line

You don't need perfect data, unlimited budget, or deep AI expertise to start.

You need:

- One painful problem
- Decent data about it
- Someone invested in solving it
- Focused effort
- Connect with an IFS AI expert

The best time to start was six months ago. The second best time is now

Every moment you wait, your competition gains ground.

Questions?

Learn More

Based on patterns from IFS Cloud implementations. Results vary by situation, data quality, and commitment.

About IFS

IFS is the world's leading provider of Industrial AI and enterprise software for hardcore businesses that make, service, and power our planet. Our technology enables businesses which manufacture goods, maintain complex assets, and manage service-focused operations to unlock the transformative power of Industrial AI™ to enhance productivity, efficiency, and sustainability.

IFS Cloud is a fully composable AI-powered platform, designed for ultimate flexibility and adaptability to our customers' specific requirements and business evolution. It spans the needs of Enterprise Resource Planning (ERP), Enterprise Asset Management (EAM), Supply Chain Management (SCM), and Field Service Management (FSM). IFS technology leverages AI, machine learning, real-time data and analytics to empower our customers to make informed strategic decisions and excel at their Moment of Service™.

IFS was founded in 1983 by five university friends who pitched a tent outside our first customer's site to ensure they would be available 24/7 and the needs of the customer would come first. Since then, IFS has grown into a global leader with over 7,000 employees in 80 countries. Driven by those foundational values of agility, customer-centricity, and trust, IFS is recognized worldwide for delivering value and supporting strategic transformations. We are the most recommended supplier in our sector. Visit ifs.com to learn why.

See IFS in action

Discover

Production: July 2025.